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AI Literacy and Undergraduate Self-Perceived Employability: Roles of AI Competency, Career Decision-Making Self-Efficacy, and Growth Mindset

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Abstract

The rapid integration of AI into contemporary workplaces has intensified the importance of AI-related capabilities for graduate self-perceived employability (SPE). Drawing on Social Cognitive Career Theory, this study conceptualizes AI literacy (AIL) as a foundational resource shaping undergraduate students' AI competency (AIC), career decision-making self-efficacy (CDMSE), and SPE. In addition, the study examines the moderating role of growth mindset (GM) in strengthening the relationships between AIL and both AIC and CDMSE. Using a quantitative research design, survey data were collected from 381 undergraduate students in China. The findings indicate that AIL is positively associated with AIC and CDMSE. Both AIC and CDMSE are significant predictors of SPE, while AIC also shows a positive association with CDMSE. Moreover, GM enhances the positive effects of AIL on AIC and CDMSE. This study contributes to career development and SPE scholarship and offers practical implications for higher education institutions aiming to better prepare students for AI-driven labor markets.

1. Introduction

In contemporary higher education, SPE has become a central outcome reflecting how well undergraduates are prepared to transition from university to sustainable employment. For university students, SPE remains a primary concern, as many graduates face challenges in securing employment upon completing their studies. Consequently, SPE is widely regarded as a key indicator of educational quality, reflecting students' perceived control, confidence, and preparedness to pursue meaningful career opportunities (Cheung et al., 2020).

The swift integration of AI into various sectors has heightened the necessity for university students to develop AI literacy (hereafter AIL) (Hornberger et al., 2023; Kong et al., 2023). Prior research highlights a strong link between AIL and student SPE in higher education contexts. For example, Wut et al. (2025) identified a significant positive association between AIL and SPE among university students in Hong Kong, underscoring the need for higher education institutions to align curricula with emerging labor market demands that increasingly require AIL.

Extant literature has emphasized the importance of equipping students with AI knowledge to keep pace with technological advancements in both professional and societal contexts a (Bewersdorff et al., 2025; Biagini, 2025; Chiu et al., 2024; Hornberger et al., 2023; Kong et al., 2023; Wang et al., 2023). Beyond general awareness of AI, students' ability to competently apply AI tools plays an increasingly important role in enhancing their SPE and workplace effectiveness. Since AI contributes value throughout almost every stage of the workplace value chain, graduates must acquire relevant skills to meet contemporary demands and improve their SPE (Drydakis, 2024).

When individuals possess a clear understanding of available career options, they are better able to anticipate potential challenges and setbacks during career exploration and to form realistic expectations about their future careers. This clarity facilitates the development of actionable career plans and enhances the quality and effectiveness of career-related decisions and behaviors (Kleine et al., 2021). Individuals with high CDMSE tend to have a clearer sense of their career goals and values, which strengthens their professional identity. In contrast, those with low CDMSE are more likely to question their abilities and choices during the decision-making process, leading to uncertainty that can impede career development (Kvasková et al., 2023). This study argues that undergraduate SPE is also influenced by students' confidence in their ability to make informed and effective career decisions in uncertain and rapidly evolving job markets.

Student growth mindset (hereafter GM) has emerged as a critical psychological resource that shapes how undergraduates approach learning, skill development, and career preparation in rapidly changing, technology-driven environments. Although GM has not been found to exert a strong direct effect on academic performance, existing research suggests that it plays a meaningful indirect role by strengthening self-beliefs and regulating effort investment (Ba et al., 2025). This study argues that GM plays a moderating role by strengthening the effects of AIL on students' AIC and CDMSE in the context of SPE development.

Despite AI's growing prominence, empirical research examining students' perceptions of AI in relation to education and career development remains limited (Santos-Jaén et al., 2025). While prior studies have extensively documented AI's role in corporate automation and efficiency, comparatively little attention has been devoted to understanding how students interpret these developments or how such perceptions influence their educational decisions and career aspirations (Santos-Jaén et al., 2025).

Investigating these perceptions is therefore critical, as they may shape students' motivation to acquire AI-related competencies and adapt to an increasingly AI-mediated labor market. This study makes several contributions to the literature on graduate SPE and career development. First, it advances understanding of AI-related SPE by empirically conceptualizing AIL as a foundational resource that shapes undergraduate students' AIC and CDMSE in AI-driven labor markets. Second, by grounding the model in Social Cognitive Career Theory (SCCT), the study clarifies the interrelationships among AIL, AIC, CDMSE, and perceived SPE. Third, the study extends prior research by demonstrating the moderating role of GM, highlighting how psychological resources strengthen the impact of AIL on key career-related capabilities.

2. Theoretical background and hypothesis development

This study draws on SCCT to examine the effects of AIL on undergraduate students' AIC and CDMSE, and to assess how these factors contribute to perceived SPE. It also examines the moderating role of GM in strengthening the relationships between AIL and both AIC and CDMSE. SCCT elucidates how individuals form career interests, make career-related choices, and achieve career success by emphasizing the interplay of cognitive processes, learning experiences, and social–contextual influences and emphasizes the central roles of self-efficacy, outcome expectations, and goal-setting in career development processes (Cardoso et al., 2013).

In career settings, self-efficacy plays a critical role in determining whether individuals initiate, sustain, and succeed in particular career trajectories (Schaub & Tokar, 2005). In addition, SCCT proposes that outcome expectations—individuals' beliefs regarding the likely consequences of engaging in particular career behaviors—shape motivation and influence career choices. Alongside personal goals, which represent intentions to attain specific career outcomes, these cognitive components interact to guide the development of career interests and decision-making processes (Schaub & Tokar, 2005). By fostering AIL and AIC and reinforcing CDMSE, the SCCT framework explains how these interconnected factors contribute to stronger SPE perceptions. In line with SCCT, AIL functions as an important learning experience that supports skill acquisition and strengthens self-efficacy beliefs, which in turn contribute to students' perceived SPE as a proximal career outcome.

2.2. AIL and AIC

AIL has rapidly become a core component of higher education, reflecting the expanding influence of AI across society, labor markets, and academic disciplines (Bewersdorff et al., 2025; Kong et al., 2023; Laupichler et al., 2022). Accordingly, AI-literate students not only understand how AI technologies function but are also able to apply them responsibly and critically assess their broader societal implications (Kong et al., 2023; Laupichler et al., 2022). The use of AI within digital–physical contexts enables students to access career-related resources and enhance field-specific competencies (Asad & Anwar, 2025). Graduates with strong AIL are therefore better equipped not only to operate AI tools, but also to evaluate when and why their use is appropriate, thereby strengthening practical competence.

Empirical evidence supports this progression from literacy to competency, with prior studies indicating that foundational literacy precedes and facilitates skill development (Laupichler et al., 2022; Sanusi et al., 2022). Research in educational technology further demonstrates that individuals with higher levels of AIL exhibit greater confidence and competence in applying AI across academic, professional, and problem-solving contexts (Kong et al., 2023; Singh et al., 2025). Furthermore, although AIL reflects individuals' conceptual understanding of artificial intelligence, AIC represents the ability to translate such understanding into practical and actionable skills. The linkage between AIL and AIC can be explained through cognitive development perspectives, particularly knowledge scaffolding, which suggests that foundational knowledge provides the basis for the acquisition of more advanced skills (Hornberger et al., 2023). Accordingly, this study proposes the following hypothesis:

H1a: AIL is positively associated with AIC of undergraduates.

2.3. AIL and CDMSE

AI applications in higher education require adaptive learning platforms, individualized learning, and virtual intelligent learning environments (Ghnemat et al., 2022). This advancement has transformed the paradigm of traditional education away from traditional courses and toward enhanced AI learning environments, which may increase students' learning and learning outcomes

while also optimizing managerial and administrative duties (Kuka et al., 2022). Existing research suggests that students generally view organizational AI adoption as a driver of enhanced performance through automation and improved decision-making, which, in turn, generates new avenues for learning and professional development (Santos-Jaén et al., 2025). In addition, AIL enhances problem-solving and decision-making abilities, which constitute key dimensions of AIC (Casal-Otero et al., 2023).

A fundamental requirement for the effective integration of AI in education is a nuanced understanding of students' perceptions of AI and how these perceptions correspond to emerging professional expectations (Santos-Jaén et al., 2025). Additionally, AI-supported learning has been shown to enhance students' computational thinking and programming self-efficacy (Yilmaz & Karaoglan Yilmaz, 2023). Despite these advances, empirical studies investigating the intersection of AI and career development within higher education remain limited, revealing a notable gap in the literature (Maulana et al., 2025).

H1b: AI literacy is positively related to the CDMSE of undergraduates.

2.4. AIC and SPE

The impact of AI on careers is substantial, as it is expected to create new occupations and industries while transforming or displacing existing roles, necessitating the development of new skills and potentially rendering some competencies obsolete (Behrend et al., 2024; Donald et al., 2024; Selenko et al., 2022). Supporting a more optimistic view, Kemp (2024) argues that AI can enhance human capital and generate competitive advantages through intelligent automation. However, Portocarrero et al. (2025) also note that many graduates lack formal training to fully leverage AI's potential, relying instead on self-directed learning and online platforms.

Prior research shows that AI training provides young professionals with a clear advantage in securing employment opportunities (Biagini, 2025; Hornberger et al., 2023; Kong et al., 2023), while the concept of AI Capital underscores how AI-related knowledge and skills translate into greater access to job interviews and higher-quality employment outcomes (Drydakis, 2024). In line with these findings, AIC signals to employers that graduates can leverage technology to improve productivity and innovation, aligning with increasing labor market expectations. As AI-related skills are now commonly required in graduates' educational profiles (Wut et al., 2025), students with higher AIC are more likely to perceive themselves as employable and well prepared for AI-driven workplaces. By demonstrating the ability to understand and apply AI tools, students are more likely to perceive themselves as capable of meeting employer expectations and adapting to technology-intensive work environments. Therefore, the following hypothesis is stated as follows:

H2a: AIC is significantly related to SPE.

As students develop AI-related competencies, they gain clearer insights into technology-driven career options and feel more confident in assessing their abilities relative to labor market demands. Empirical evidence provides strong support for the AI Capital framework, showing that AIL—alongside AI-related knowledge, skills, and targeted educational interventions—positively impacts students' digital self-efficacy, competencies, ethical awareness, confidence in using AI technologies, academic performance, and SPE (Bewersdorff et al., 2025; Biagini, 2025; Drydakis, 2024; Hornberger et al., 2023; Kong et al., 2023; Wang et al., 2023). Research further indicates that generative AI technologies contribute to career resilience and professional competencies (Kong et al., 2024), underscoring the growing importance of higher education institutions in preparing future human capital (Laupichler et al., 2022). Higher AIC therefore supports the intrinsic motivation and proactive career behaviors associated with stronger CDMSE (Ran et al., 2023). Building on this relationship, this study argues that AIC strengthens CDMSE by enabling students to engage more proactively and strategically in career planning and exploration. Hence, the current study intends to empirically examine the following hypothesis:

H2b: AI competency is significantly related to Career Decision-Making Self-efficacy.

2.5. CDMSE and SPE

Prior research consistently demonstrates that CDMSE plays a central role in students' career development and SPE. Students with higher CDMSE are more likely to formulate structured career plans, engage in proactive career exploration and preparation, and display adaptive career attitudes and behaviours (Jiang et al., 2024; Kleine et al., 2021). Empirical studies across diverse

contexts show that CDMSE is a strong predictor of multiple dimensions of SPE, reflecting students' confidence in making effective career decisions (Tiraieyari & Abdul Hamid, 2015; Zhou et al., 2023, 2025). Moreover, CDMSE functions as a key psychological mechanism that motivates effort, persistence, and goal-directed behavior, thereby supporting students' career readiness and long-term career success (Duru & Söner, 2024; Kvasková et al., 2023). This study predicts that CDMSE positively influences student SPE by enhancing students' confidence in exploring career options, setting achievable goals, and making informed career decisions. Students with stronger CDMSE are expected to engage more actively in career-related learning, skill development, and labour-market exploration, enabling them to better align their competencies with employer expectations and navigate career transitions effectively, ultimately strengthening their SPE outcomes. Accordingly, the following hypothesis is derived as follows:

H3: CDMSEis positively related to SPE.

2.6. Moderating role of GM

By fostering a GM, students are more likely to maintain motivation, strengthen confidence in their abilities, and persist in pursuing goals (Lai et al., 2022). Students with a fixed mindset, in contrast, perceive intelligence as a stable trait that cannot be substantially altered through effort or learning whereas those with a GM believe that intelligence can be developed through practice, effort, and continuous learning (Sousa & Clark, 2025). This belief encourages adaptive learning strategies, resilience in the face of challenges, and engagement with difficult tasks, thereby supporting deeper academic involvement and higher achievement (Sousa & Clark, 2025).

Dweck (2006) conceptualized mindset as comprising two orientations—fixed and growth—distinguished by beliefs about the malleability of ability and intelligence. Individuals with a GM view abilities as developable through effort, perseverance, and learning, a perspective that has become central in educational and psychological research. A growing body of evidence demonstrates that GM positively influences students' cognitive, motivational, and developmental outcomes (Jin et al., 2025), prompting increased scholarly attention to the conditions that foster its development.

Yeager and Dweck (2020) emphasized that this mindset reframes effort as a mechanism for skill improvement, leading to adaptive changes in thinking, behavior, and performance. Recent research extends these findings to technology-related contexts, indicating that GM predicts engagement with emerging technologies, including generative AI (Chow & To, 2025), and positively influences attitudes toward and intentions to use tools such as ChatGPT (Dinh, 2024). Growth-minded individuals also demonstrate stronger self-regulated learning behaviors, including feedback seeking, information exploration, and persistence following failure, which enhance performance expectancy (Orosz et al., 2023). More broadly, mindsets are motivational beliefs about the malleability of personal attributes, such as intelligence and personality (Dweck, 2008). These beliefs exist along a continuum from a fixed mindset, which construes abilities as stable and immutable, to a GM, which emphasizes development through effort and learning. Extensive research indicates that students with a GM are more likely to value effort, persist in the face of challenges, and engage actively in learning activities (Xu et al., 2025). In contrast, a fixed mindset is associated with maladaptive learning behaviors, including avoidance, procrastination, and disengagement when difficulties arise (Dweck, 2006). Building on this framework, Yeager and Dweck (2020) argued that learners with a GM believe intellectual abilities can be developed through sustained practice and perseverance. Therefore, this study aims to test the following hypothesis:

H4a: GM strengthens the relationship between AI literacy and AI competency, such that the relationship is stronger at a higher level of GM.

As students develop greater awareness of a GM, their willingness to invest effort and capacity to enhance performance increase, contributing to improved academic achievement (Ma et al., 2024). A GM encourages individuals to view intelligence as malleable and emphasize continuous improvement, whereas a fixed mindset is associated with self-doubt and discouragement regarding one's abilities (Ba et al., 2025; Hecht et al., 2024). Empirical evidence suggests that GM is generally a stronger predictor of academic performance than fixed mindset, as growth-oriented students tend to prioritize learning goals that support positive academic outcomes. GM can buffer the negative effects of stereotypes and promote persistence, resilience, and adaptive learning behaviors (Chen et al., 2024). Nevertheless, some evidence suggests that the direct effects of GM on academic

achievement may be modest. Beyond performance outcomes, students with a GM often report greater confidence in their future academic success, which elevates expectations and indirectly enhances achievement (Ba et al., 2025).

Students who internalize a GM exhibit greater confidence in overcoming academic challenges, thereby establishing a psychological foundation for sustained academic success (Sheffler & Cheung, 2024). Consistent with this perspective, learners with a GM report higher levels of self-efficacy than their fixed-mindset counterparts (Yu-chu et al., 2023). In addition, GM supports self-regulation, particularly in contexts requiring sustained effort and perseverance (Zarrinabadi et al., 2022). Extending this line of inquiry, recent evidence suggests that a GM toward self-regulation enables individuals to construe effortful self-control as a constructive strategy for maintaining persistence over time (Derakhshan & Fathi, 2024). Based on the above argumentation, this study intends so empirically test the following sub-gypothesis:

H4b: GM strengthens the relationship between AI literacy and Career Decision-Making Self-efficacy, such that the relationship is stronger at a higher level of GM.

3. Research methods

3.1. Data collection

This study employed a cross-sectional survey design using convenience sampling. The target population comprised undergraduate students enrolled in higher education institutions in China. Three inclusion criteria guided participant selection: participants had to be full-time undergraduates, have completed at least one year of university study to ensure adequate exposure to digital learning and career-related experiences, and possess basic familiarity with digital learning tools commonly used in Chinese universities.

Data were collected from undergraduate students in seven universities in Zhejiang Province, China, using a structured questionnaire. With the assistance of lecturers and senior students, questionnaires were distributed and collected during class sessions, resulting in a high response rate and minimizing common issues associated with online surveys, such as low engagement, incomplete responses, and non-response bias. The instrument was developed in English and translated into Chinese using a back-translation procedure to ensure linguistic and conceptual equivalence.

Table 1
Undergraduate Students' Profile

Characteristics	Categories		Percent
Gender	Male	174	45.6%
	Female	207	54.39%
Major of Study	Business Administration	92	24.12
	Science and Medicine	89	23.38
	Engineering and Architecture	81	21.18
	Arts and Law	58	15.32
	Social Sciences	36	9.40
	Education	33	8.60
Experience with using AI applications	Basic experience	66	17.40
	Moderate experience	113	29.60
	High experience	143	37.65
	Very high experience	59	15.35
Year of Study	Year 2	85	22.2
	Year 3	114	30
	Year 4	133	35
	Year 5 or above	49	13

A total of 443 questionnaires were distributed, yielding 381 usable responses after screening for incomplete or invalid entries, resulting in an effective response rate of approximately 86%. The high response rate is likely due to in-class administration, the relevance of the survey topic to students' academic and career development, and the immediate collection of completed questionnaires. The valid sample shown in Table 1 demonstrates a balanced and diverse demographic profile that supports the robustness of the study findings. In terms of gender, female students (54.39%) slightly outnumber male students (45.6%), reflecting the gender composition commonly observed in many Chinese universities and suggesting that the sample is not heavily skewed toward one gender. Regarding academic majors, participants were drawn from a wide range of disciplines, with the largest proportions from Business Administration (24.12%), Science and Medicine (23.38%), and Engineering and Architecture (21.18%). This disciplinary diversity is appropriate given the study's focus on AIL and SPE, as AI-related competencies are increasingly relevant across both STEM and non-STEM fields. Students from Arts and Law (15.32%), Social Sciences (9.40%), and Education (8.60%) were also represented, indicating that the sample captures perspectives beyond traditionally technology-intensive disciplines. This breadth strengthens the generalizability of the findings across different academic contexts. With respect to experience using AI applications, the majority of respondents reported moderate to high levels of experience, with 29.60% indicating moderate experience, 37.65% high experience, and 15.35% very high experience, while only 17.40% reported basic experience. This distribution aligns well with the study's assumption that participants possess baseline AIL and reflects the widespread integration of AI tools into students' learning activities. Finally, the distribution across years of study shows that most respondents were in their later years of undergraduate education, with 35% in Year 4 and 30% in Year 3, followed by Year 2 (22.2%) and Year 5 or above (13%). This pattern is justified, as senior students are more likely to have accumulated academic experience, exposure to AI-related technologies, and clearer perceptions of SPE.

3.2 Measures

This study employed established measures from prior literature to operationalize all constructs. AIL was conceptualized as students' ability to understand, use, and critically evaluate AI tools and was measured with four items adapted from Li et al.

(2022), capturing foundational knowledge and procedural understanding. AIC was defined as the ability to effectively apply and manage AI, assessed via four items adapted from Sanusi et al. (2022), evaluating confidence in using AI-enabled software, managing information, problem-solving, and analyzing and presenting data. CDMSE reflects individuals' confidence in performing tasks related to making and committing to career decisions, and was measured using three items adapted from Lent et al. (2016), capturing confidence in handling challenges and constraints in career decision-making. GM was measured using a six-item scale adapted from Ting and Yeh (2023), assessing beliefs in the malleability of creativity and the capacity to enhance skills through effort and learning. SPE refers to individuals' evaluations of their capacity to obtain and retain employment based on their skills, experiences, and prevailing labor market conditions (Rothwell & Arnold, 2007). SPE serves as a key psychological resource that supports students during university and in the school-to-work transition, capturing how internal capabilities and external opportunities are integrated in judgments of employment prospects (De Vos et al., 2011; Lo Presti et al., 2020). Hence, Students' SPE was operationalized as students' career preparedness, measured with a five-item scale adapted from (Bennett & Ananthram, 2022), assessing understanding of career prospects, work procedures, career mobility, and goal-oriented actions. All constructs were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

4. Results and Analyses

4.1 data analysis procedure

Data analysis was conducted in three sequential phases. First, confirmatory factor analysis (CFA) assessed the measurement model by examining factor loadings, reliability, and validity, ensuring the robustness of the instruments. Second, potential common method bias (CMB) was addressed, and model fit was evaluated using goodness-of-fit indices to confirm the adequacy of the proposed four-factor measurement model. Finally, structural equation modeling (SEM) was applied to test the structural model based on the theoretical framework, allowing for the examination of direct relationships as well as the moderating effects among the study constructs.

Table 2
Results of measurement analysis.

Constructs	Items	CA	CR	AVE	Sample Item
AIL	4	0.924	0.926	0.737	I know how to access or obtain AI tools that are relevant for learning or future work
GM	6	0.907	0.901	0.761	I can improve my creative ability through self-learning.
AIC	4	0.879	0.872	0.574	I am confident in my ability to use AI-enabled software or systems to complete academic or work-related tasks.
CDMSE	8	0.936	0.931	0.632	I can figure out which career options could provide a good fit for my personality.
EMP	5	0.828	0.824	0.546	I understand the future career development prospects.

4.2 Reliability and validity analysis

Reliability and validity were assessed using SPSS 23.0 and AMOS 23.0. Construct reliability, convergent validity, and discriminant validity were systematically evaluated. As shown in Table 2, all constructs exhibited average variance extracted (AVE) values above 0.50 and composite reliability (CR) values exceeding 0.70, indicating satisfactory reliability (Hair et al., 2012). Cronbach's alpha coefficients were also above 0.70, confirming internal consistency. Confirmatory factor analysis demonstrated that all items loaded significantly onto their intended constructs, with standardized factor loadings above 0.60, supporting convergent validity (Fornell & Larcker, 1981) as shown in Table 2. Discriminant validity was verified through cross-loading analyses, which showed that items loaded more strongly on their respective constructs than on others, and via the Fornell–Larcker criterion, where the square root of each AVE exceeded inter-construct correlations (Table 3). Overall, these results indicate that the measurement model possesses satisfactory reliability, convergent validity, and discriminant validity.

Table 3
Correlation matrix, mean, and standard division.

Construct	Mean	SD	1	2	3	4	5	6	7	8	9
1. AI Literacy	3.487	0.982	**0.854**								
2. GM	2.715	1.137	−0.257**	**0.871**							
3. AI Competency	3.927	0.653	0.255**	−0.204**	**0.754**						
4. DMSE	4.011	0.635	0.363**	−0.143**	0.317**	**0.854**					
5. SPE	4.072	0.687	0.103*	−0.234**	0.156**	0.202**	**0.774**				
6. Gender	NA	NA	−0.033	0.083	0.047	0.068	0.024	**NA**			
7. Major	NA	NA	0.092	0.127**	0.002	0.031	0.079	0.260**	**NA**		
8. AI experience	NA	NA	0.020	0.067	0.100*	0.133**	−0.022	−0.114*	−0.127**	**NA**	
9. Year of Study	NA	NA	0.029	−0.157	−0.079	−0.049	−0.019	0.043	0.042	−0.042	**NA**

Note. The square root of the AVE of all constructs are shown in bold and diagonals; $_{*}p < 0.05$, $_{**}p < 0.01$.

4.3. Assessment of common method bias (CMB)

After establishing the reliability and validity of the measurement model, several procedural and statistical techniques were applied to mitigate potential common method bias (CMB), following Podsakoff et al. (2012). Procedurally, survey items were randomized and anonymity was assured to reduce evaluation apprehension and socially desirable responses (Hair et al., 2012). Statistically, Harman's single-factor test indicated five distinct factors, with the first factor accounting for only 27.86% of total variance, suggesting minimal CMB. Further assessment using the CFA marker technique showed poor fit for a single-factor model ($\chi^2 = 7466.860$, df = 365, RMSEA = 0.209, CFI = 0.510, TLI = 0.455, IFI = 0.511), confirming that a one-factor solution did not adequately explain the data and that CMB was unlikely to bias results. Finally, variance inflation factor (VIF) values were all below 10, indicating no multicollinearity issues (Kock, 2015).

4.4. CFA analysis

To assess the variability of the study variables at the individual level, confirmatory factor analysis (CFA) was conducted. As shown in Table 5, the hypothesized five-factor measurement model exhibited a good fit to the data ($X^2 = 1083.546$, df = 355, CFI = 0.941, TLI = 0.942, RMSEA = 0.068). These fit indices indicate that the five-factor model provides a superior fit compared to alternative models, thereby supporting the discriminant validity of the constructs (Kock, 2015).

Table 4
Factors loadings and cross-loadings.

Constructs	Items	CDMSE	AIL	AIC	GM	EMP
CDMSE	CDMSE1	**0.964**	0.032	0.014	0.024	−0.009
	CDMSE2	**0.961**	0.031	0.003	0.028	−0.019
	CDMSE3	**0.947**	0.018	0.008	0.025	−0.007
	CDMSE4	**0.908**	0.027	0.014	−0.067	−0.029
	CDMSE5	**0.901**	−0.028	0.032	−0.063	−0.022
	CDMSE6	**0.616**	0.204	−0.105	0.014	0.065
	CDMSE7	**0.688**	0.137	0.086	0.071	0.107
	CDMSE8	**0.616**	0.097	0.068	0.035	0.072
AIL	AIL1	−0.008	**0.927**	−0.049	−0.037	−0.012
	AIL2	−0.031	**0.896**	−0.018	-0.009	-0.052
	AIL3	0.006	**0.841**	0.081	0.059	0.017
	AIL4	0.096	**0.665**	−0.069	−0.091	−0.039
AIC	AIC1	−0.058	0.034	**0.843**	−0.086	0.062
	AIC2	−0.049	0.032	**0.837**	−0.093	0.058
	AIC3	0.033	−0.026	**0.764**	0.145	0.046
	AIC4	0.022	0.102	**0.762**	−0.019	0.033
GM	GM1	0.005	0.031	0.039	**0.943**	−0.017
	GM2	−0.002	0.048	0.047	**0.931**	−0.014
	GM3	−0.018	−0.009	−0.062	**0.852**	−0.023
	GM4	0.026	−0.097	0.023	**0.749**	−0.005
	GM5	−0.029	−0.035	0.019	**0.712**	0.018
	GM6	0.083	0.082	0.075	**0.633**	0.076
SPE	EMP1	−0.032	0.024	−0.056	0.011	**0.936**
	EMP2	−0.038	0.018	−0.047	0.012	**0.932**
	EMP3	−0.020	0.083	0.003	−0.047	**0.674**
	EMP4	0.050	−0.109	0.026	−0.098	**0.653**
	EMP5	0.122	0.064	0.095	0.067	**0.607**

Note. All item loadings were significant at the $p < 0.001$ level.

4.5. Assessment of structural model

The structural model of the study was assessed by examining the path relationships, effect sizes, and predictive relevance of the model. All proposed hypotheses were analyzed using AMOS software version 23.0, employing the fundamental SEM analytical procedures, and the results are displayed in Fig. 1. Consistent with previous studies guide- lines (Hair et al., 2016), the individual construct regression coefficient was computed. Figure 2 visualizes the regression findings using the standardized path coefficients and significance levels.

The empirical finding suggests a significant relationship between AIL and AIC (B = 0.285; t = 5.974; p < 0.001), and CDMSE (B = 0.372; t = 8.329; p < 0.001) supporting H1a and H1b. Additionally, a positive association is observed between AIC (B = 0.108; t = 2.316, p < 0.05), and SPE, H2a is validated by this finding. AIC is also significantly related to CDMSE (B = 0.261; t = 4.981, p < 0.001), H2b is also supported by this study. Similarly, results illustrated that CDMSE is significantly related to SPE (B = 0.159; t = 3.683, p < 0.001), thereby H2c is supported by this finding. Overall, the findings confirm the proposed structural relationships among AIL, AIC, CDMSE, and undergraduate SPE. Finally, the findings indicate that undergraduate students with higher levels of CDMSE tend to hold stronger career aspirations and are therefore better positioned to achieve their career-related goals.

Table 5
Confirmatory factor analysis.

Models	χ^2	*df*	REMSA	TLI	CFI	IFI
One-factor model	7467.87	358	0.21	0.46	0.51	0.52
Two-factor model	6204.51	357	0.19	0.57	0.59	0.61
Three- factor model	4289.82	354	0.15	0.70	0.72	0.74
Four- factor model	3032.19	351	0.12	0.80	0.81	0.82
Five-factor model	1084.55	347	0.07	0.95	0.95	0.96

Note. Four-factor model: combined SPE, and CDMSE; three-factor model: combined SPE, CDMSE and AIC; two-factor model: combined SPE performance, CDMSE, AIC, and AIL, RMSEA: Root Mean.

4.6. GM as a moderator

Moreover, the moderating role of GM in the relationship between AIL and key outcomes was examined using moderation analysis procedures recommended by Hair et al. (2017). It was hypothesized that GM moderates the effects of AIL on both AIC and CDMSE. As illustrated in Fig. 2, GM significantly strengthened the association between AIL and AIC, as indicated by a significant interaction effect (B = 0.155, t = 3.839, p < 0.001).

In addition, GM was found to strengthen the relationship between AIL and career decision making self-efficacy, supported by the significance of the interaction term (B = 0.171, t = 4.106, p < 0.001). Taken together, these findings provide empirical support for hypotheses H3a and H3b. Finally, Figs. 3 and 4 illustrate the moderating effect of GM. As shown in Fig. 2, higher levels of GM strengthen the positive linear relationship between AIL and AIC. Likewise, Fig. 3 shows that GM strengthens the positive linear association between AIL and CDMSE. These findings highlight the importance of cultivating GMs, supportive learning environments, and effective effort-regulation strategies to promote both academic achievement and long-term career development.

5. Discussion

This study examined how AIL influences undergraduate students' AIC, CDMSE, and perceived SPE, while also exploring the moderating role of GM. The findings provide robust empirical support for the proposed relationships and highlight the combined importance of technological and psychological resources in shaping SPE in AI-driven labor markets. Specifically, AIL was found to be positively associated with both AIC and CDMSE, emphasizing the role of foundational AI understanding in fostering practical skills and career-related confidence. In line with SCCT, AIL functions as a critical learning experience that strengthens capability beliefs and competency development, extending SPE research by positioning AIL as a key antecedent of career-related skills and self-efficacy rather than merely technical knowledge.

Second, the results show that both AIC and CDMSE are significant predictors of perceived SPE, indicating that students' SPE perceptions are shaped by a combination of technological skills and confidence in managing career decisions within dynamic labor markets. The positive relationship between AIC and CDMSE further suggests that the development of AI-related skills reinforces students' beliefs in their ability to make effective career choices, consistent with the reciprocal mechanisms proposed by SCCT. These findings underscore the interactive role of skill mastery and psychological resources in shaping SPE perceptions.

Third, the findings identify GM as a significant moderator that strengthens the effects of AIL on both AIC and CDMSE. This highlights the importance of adaptive learning beliefs in enhancing the impact of AIL, as students with stronger GMs are more capable of converting AI-related knowledge into practical skills and career confidence. By extending GM research to the AI–SPE context, this study demonstrates that GM functions as a key boundary condition that amplifies the role of AIL in career development.

Taken together, the findings offer a more integrated explanation of undergraduate SPE in AI-intensive contexts by highlighting the joint influence of technological resources (AIL and AIC) and psychological resources (CDMSE and GM). By moving beyond SPE models that focus solely on skills or attitudes, this study demonstrates that effective SPE development in the AI era requires both access to technological learning opportunities and the cultivation of adaptive mindsets that support continuous learning and career adaptability. Overall, the study advances understanding of how AIL shapes SPE-related outcomes within the framework of SCCT and clarifies the conditions under which these effects are strengthened through GM. In addition, the positive relationship identified between AIL and graduate competencies aligns with prior findings reported by Singh et al. (2024), further reinforcing the robustness of this association.

6. Implications

6.1 Theoretical Implications

This study offers important theoretical implications for career development and SPE research. By empirically conceptualizing AIL as a foundational resource within SCCT, the findings extend the theory to AI-driven labor markets and illustrate how domain-specific technological literacy supports competency development and career-related self-efficacy. The significant relationships among AIC, CDMSE, and perceived SPE further reinforce the central role of skill mastery and capability beliefs in SPE formation, while clarifying their interrelated functions. Moreover, the moderating role of GM advances theory by identifying psychological adaptability as a critical boundary condition that amplifies the impact of AIL. Collectively, these insights offer a more integrated theoretical explanation of how technological and psychological resources jointly shape students' responses to evolving career demands.

6.2 Practical Implications

The findings provide important practical implications for higher education institutions, educators, and policymakers aiming to strengthen graduate SPE in AI-intensive environments. Universities should prioritize AIL as a core graduate capability by integrating AI-related knowledge and applied learning experiences across disciplines, rather than limiting them to specialized technical programs. In addition, curricular and career development initiatives should emphasize the enhancement of AIC and CDMSE through experiential learning, career-focused AI applications, and structured career reflection. The moderating role of GM further suggests that SPE interventions are likely to be more effective when supported by pedagogical practices that foster adaptive learning beliefs, including formative feedback, resilience-oriented activities, and mindset-informed teaching. Collectively, these approaches can better equip undergraduates with the technical skills and psychological readiness needed to succeed in AI-driven labor markets.

7. Conclusion, Limitations and future research directions

Drawing on survey data from 381 undergraduate students in China, this study examined the relationships among AIL, AIC, CDMSE, and perceived SPE. The results show that AIL has significant positive effects on both AIC and CDMSE, highlighting its foundational role in students' career development. AIC and CDMSE each positively predict perceived SPE, underscoring the joint importance of technical skills and psychological resources. In addition, AIC is positively associated with CDMSE, indicating a reinforcing link between technical proficiency and career-related confidence. The findings further reveal that GM strengthens the effects of AIL on both AIC and CDMSE, emphasizing the role of adaptive beliefs in maximizing the benefits of AI-related learning. Overall, these results provide a nuanced understanding of how AIL contributes to undergraduate SPE in the Chinese higher education context.

While the findings align with prior research linking AI use to perceived gains in SPE (Jia et al., 2024; Voigt & Strauss, 2024), the cross-sectional design precludes causal inference. This limitation does not diminish the contribution of the study; rather, it highlights the need for future research using larger and more diverse samples, longitudinal or experimental designs, and inter-institutional or cross-cultural comparisons to enhance internal and external validity (Donald et al., 2024). Nonetheless, the results support the growing consensus that AI is a pivotal factor in the development of students' career competencies and career-related resources in technologically advanced contexts (Asad & Anwar, 2025).

Despite its contributions, this study has several limitations that suggest directions for future research. First, the cross-sectional design restricts causal inference among AIL, AIC, CDMSE, and SPE. Future studies could adopt longitudinal or experimental approaches to examine how the development of AIL influences career-related outcomes over time. Second, the reliance on self-reported data may introduce common method bias and social desirability effects. Incorporating objective indicators, such as performance-based assessments or employer evaluations, would strengthen measurement validity. Third, the findings may have limited generalizability, as the sample comprised undergraduate students from China. Cross-cultural or comparative studies across different higher education systems and labor markets are therefore recommended. Finally, future research could extend the SCCT framework by examining additional contextual and individual factors, such as institutional support, AI-enabled learning environments, and outcome expectations, to provide a more comprehensive understanding of how AIL shapes SPE.

Declarations

Ethical Approval Statement

This study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki and received ethical approval from the Research and Development Committee, School of Economics and Management, Yiwu Industrial and Commercial College, on 11 May 2025. No formal approval identification number was issued by the committee. The study protocol was reviewed and approved under the supervision of Professor Chen Yupeng and Professor Nian Yan.

Informed Consent Statement

Authors obtained a written informed consent from participants after confirmation that the data collected are solely used for academic purposes.

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Author Contribution

Conceptualization, H.L. and M.L.; methodology, H.L. and M.L.; software, H.A.; validation, M.L.; formal analysis, M.L.; investigation, H.A.; resources, H.A. and M.L.; data curation, M.L. and H.A.; writing—original draft preparation, H.A.; M.L.; writing—review and editing, H.A. and M.L.; visualization, M.L.; supervision, H.L. and M.L.; project administration, H.A. and M.L.; funding acquisition, M.L. All authors have read and agreed to the published version of the manuscript.

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Data Availability

processed data are attached as a supplementary file.

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Figures

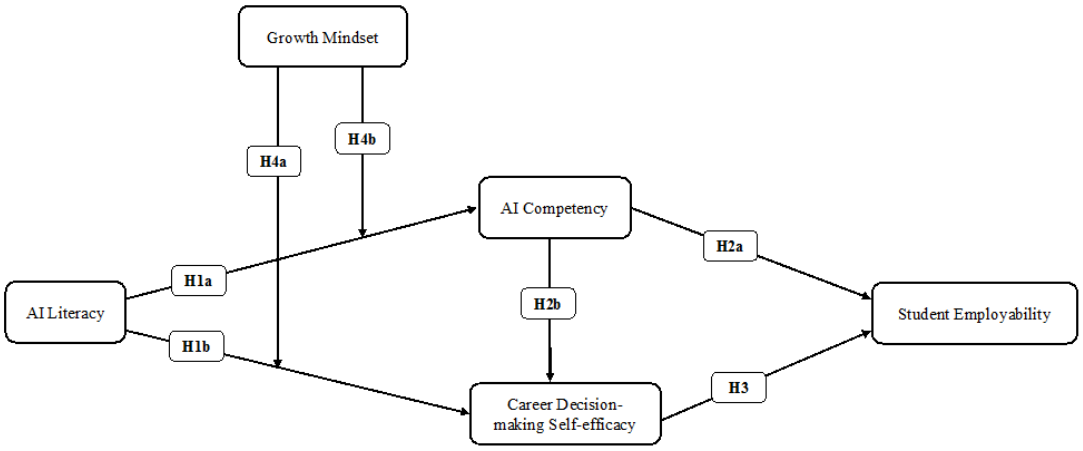


Figure 1

Research Model

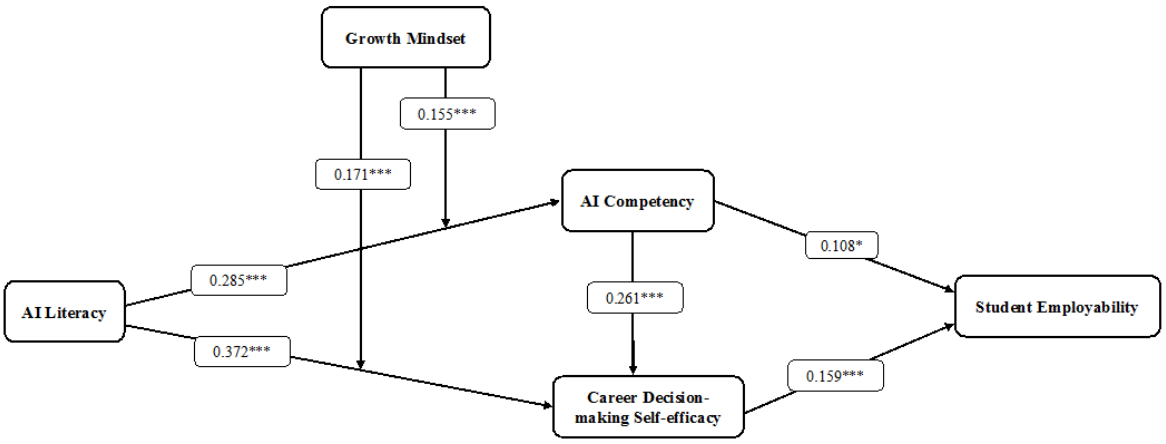


Figure 2

Hypotheses Testing Results

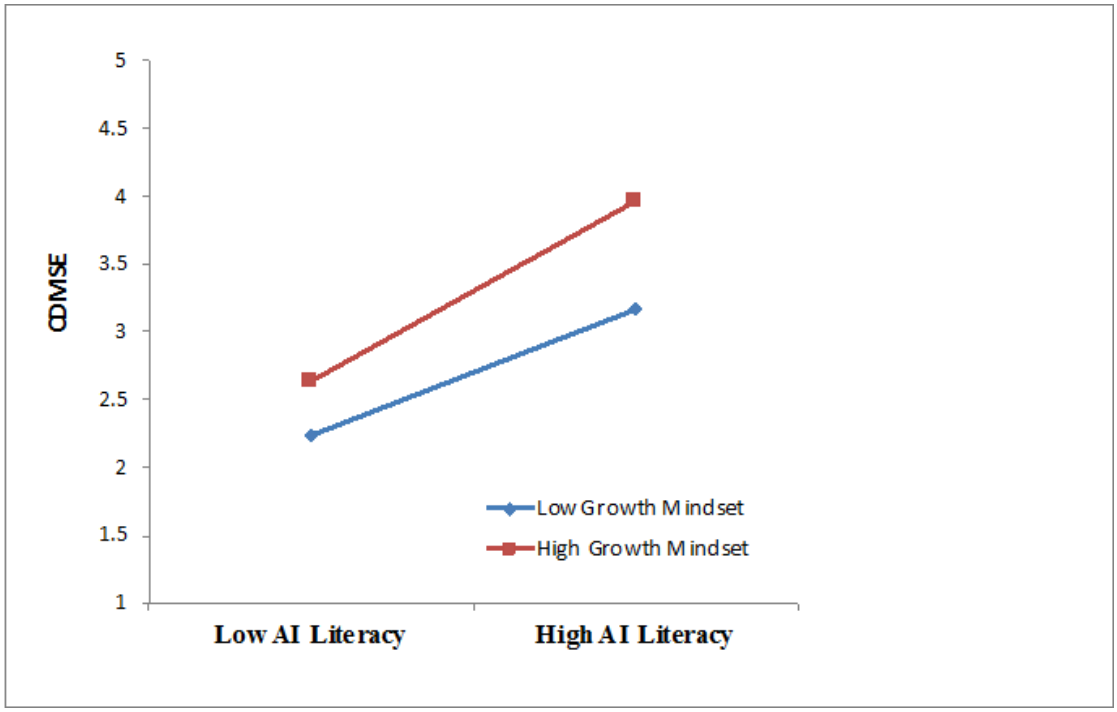


Figure 3

Moderating effect of GM in the relationship between AIL and CDMSE

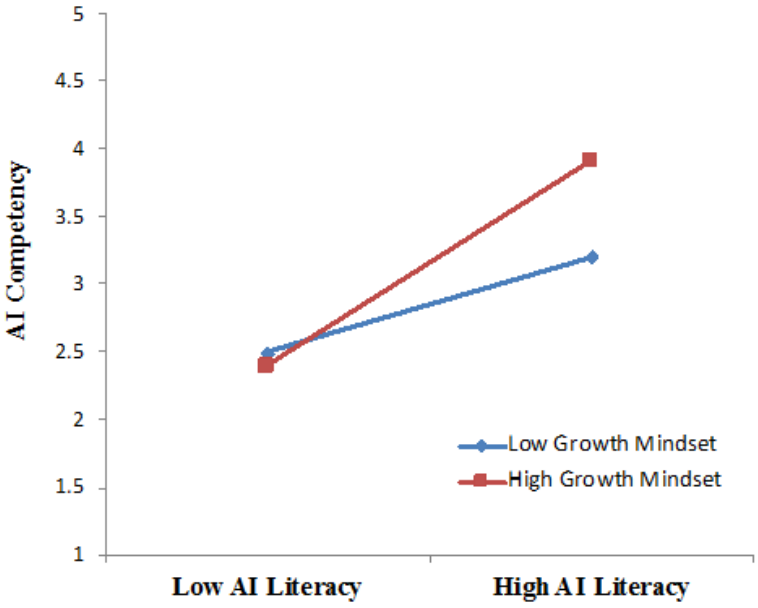


Figure 4

Moderating effect of GM in the relationship between AIL and AIC

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Survey.doc
- DataFileSurvey.xls